Implementation Guidelines for Ethologically Inspired Fuzzy Behaviour-Based Systems

Mohd Aaqib Lone, Owais Mujtaba Khanday, and Szilveszter Kovács

Abstract—**The adaptation of ethologically inspired behaviour models for human-machine interaction e.g. in Ethorobotics has become a challenging research topic in recent years. This paper presents a Fuzzy Behaviour Description Language (FBDL) approach for analyzing animal aggression behaviour. Fuzzy logic and fuzzy set theory approaches are used to analyze and classify the subjective impression of aggressive behaviour in a particular situation. This research aims to perform a meta-analysis of aggression behaviour based on the fundamental values of animals and the possible ways of implementing animal aggressive behaviour in robots. Ultimately aiming to enhance the adaptability and effectiveness of human-robot interaction and performance in various real-world scenarios, e.g., by expressing disagreement in the direction of the human operator in case of unclear, or unsafe cooperative situations. In both industrial and everyday settings, mobile robots and robotic vehicles are becoming increasingly prevalent. Integrating aggressive behaviour into robotics is essential for boosting interactions between humans and robots, promoting safety in dynamic contexts, and getting a deeper understanding of animal behaviour. It aids robots in asserting their presence, maneuvering around barriers, and efficiently adjusting to dynamic surroundings. This guarantees more seamless operations in industrial and daily environments while also enhancing our comprehension of both robotics and ethology. We present graphical depictions of various animal behaviours, as well as trajectories, Gazebo simulations, and RViz visualizations of the animal robot, demonstrating the animal's escape behaviour.**

Index Terms—**Ethologically Inspired Behavioural Models, Ethorobotics, Fuzzy Behaviour Modelling, Fuzzy Behaviour Description Language, Robot Operating System, Gazebo, RViz**

I. Introduction

Behaviour is a response to any stimulus from the situation or, in short, a way of acting in a given situation [1]. In other words, we can say that a behaviour system attempts to determine the responsive abilities of humans, animals, robots, etc., to understand and interact with the environment. The behaviour-based approach [2] aims to create intelligent robots that can carry out complex tasks into smaller, simpler behaviours or actions. These behaviours focus on the execution of specific tasks, enabling robots to carry out complex activities with greater flexibility and adaptability. This method is crucial for building robots that can function efficiently in dynamic situations characterized by quickly changing conditions. For example, in robotic navigation, one behaviour can focus on traversing a path from the start to the goal state, while another focuses on avoiding obstacles. Developing and executing individual robot behaviours is a straightforward process, which enables them to construct intricate and adaptable behaviours when paired with one another and the environment. Robots can adapt to changes in their environment and deal with uncertainty without the need for complex planning or simulations. Robots possess the ability to modify their behaviour according to various tasks and environments. This technique has a significant impact in sectors like autonomous cars, automated guided vehicles, and swarm robotics, as basic actions can result in complex collective behaviours.

Ethological modeling involves the analysis of animal behaviour based on external observations and the development of models and explanations. The behaviour-based method, when applied to ethology, aims to develop intelligent robots by emulating the innate and adaptable behaviours observed in animals. This ethological paradigm guarantees that robots can promptly and adaptively react to their environment. Nikolaas Tinbergen provides a model [3] for analyzing animal behaviour in its natural environment. The model consists of four interconnected categories of questions that provide a full framework for understanding the behaviour: The first question, "What is the function of the behaviour?" relates to the significance of the conduct in terms of adaptation. The Ethologically inspired view focuses on the selective forces that have shaped behaviour and how they impact an animal's capacity for survival and reproduction. This phase considers the physiological, genetic, and environmental factors that lead to particular behaviours. For instance, the hormonal changes that occur during bird mating behaviour or the visual cues that induce fish courtship displays. The second question, "What is the mechanism behind the behaviour?" is concerned with the physiological and neurological processes that permit the activity to occur. The animal's neurological system and how it generates, and controls behaviour are the main topics of this study. At this level, we examine the interactions between experience, environment, and genes to determine behaviour. The evolution of social behaviour in monkeys may have been influenced by early experiences. The third question, "What is the evolutionary history of behaviour?" discusses the phylogenetic origins and historical progression of behaviours. It involves the evolution of behaviours by tracing them back through the ancestors of animals across several generations. The fourth question, "What is the ontogeny of the behaviour?"

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focuses on how the behaviour developed inside a particular creature. The development, acquisition, and evolution of behaviour across an animal's lifetime are the main topics of this study. Ethology provides a valuable framework for creating behaviour models in robotics (Ethorobotics [4]) that can replicate the successful and efficient actions of animals. This field encompasses a broad range of research, including studies on animal aggression, defense mechanisms, and communication, all of which can inform the development of robotic behaviours.

In this paper, we will be discussing how we can apply fuzzy logic to simulate aggressive behaviour in animals. Fuzzy logic is a type of computing that deals with uncertain or imprecise information and relies on the degree of truth in the input to produce a specific output. It is commonly used to control actions and processes in fields such as automotive and environmental applications. An example of a state machine that employs fuzzy logic to deal with uncertainties and imprecisions in the decision-making process is the Fuzzy State Machine (FSM). Robotics extensively uses FSMs because real-time decisions must be made in an environment that is frequently dynamic and uncertain. The conventional state machine operates by switching between states in accordance with predetermined criteria. However, robotics frequently operates in uncertain environments, which means that not all precepts and conditions may apply. This is where fuzzy logic comes into play. Fuzzy logic provides a mathematical framework for managing uncertainty by assigning varying degrees of truth to propositions. In a FSM, fuzzy logic is used to express state transition rules. Fuzzy sets analyze the inputs to the FSM, allowing for gradual changes in state rather than abrupt ones. By making transitions gradual, the robot's behaviour is less likely to change suddenly, which in some situations could be risky. Robotics can benefit from the resilience, adaptability, and scalability of FSMs, among other advantages [5].

Fuzzy signatures are an advanced method for fusing fuzzy information, enabling the systematic incorporation of heterogeneous data sources into a cohesive framework [6]. In scenarios where the fused information is intricate and multifaceted, they are particularly effective. Fuzzy signatures decompose information into a hierarchical structure of characteristics, each with its own layer of fuzzy values, representing distinct aspects or components of the system under analysis. The hierarchical structure enables the aggregation of these characteristics at many levels, illustrating their interrelationships [7].

In behaviour modeling, fuzzy signatures can be particularly advantageous when the behaviours of components can be expressed using fuzzy sets. In robotic systems, actions like locomotion, manipulation, or navigation can be expressed as fuzzy signatures, effectively capturing the inherent uncertainty and unpredictability associated with such actions [8]. Once combined, these distinct fuzzy fingerprints form a unified entity that accurately reflects the robot's full behaviour, enabling more versatile and adaptable decision-making. Fuzzy signatures are suitable for applications involving intricate behaviours and the many interacting components. In human-robot interaction, they can integrate diverse elements into a cohesive representation.

In the specific behaviour example outlined in this paper, fuzzy information fusion could be suitable for behaviour fusion if the behavioural components are precisely defined using fuzzy signatures. However, the bahavioural components in our example are different activities that have no fuzzy signatures, so conventional approaches are used to manage these operations. To sum up, the FSM is a powerful tool for robotics decision-making. There are several ways to describe robot behaviour, including deliberative, reactive, hybrid, and behaviour-based control [9]. Fuzzy logic is a useful method for machine control and provides a high level of accuracy in reasoning. In the following sections of this paper, we will delve further into the implementation of fuzzy logic in simulating aggressive behaviour in animals.

In the deliberative control method, the robot uses its past experiences and current sensory information to determine the next steps it should take. This approach is also known as "Think Then Act." Decision-making for the robot involves gathering information about the environment through its sensors and using this information to determine how to act and interact with the environment. The deliberative process includes reasoning about potential actions and their consequences, as well as developing a symbolic representation of the world to anticipate the outcomes of those actions and create plans for various scenarios. Essentially, the robot uses its internal processing to carefully consider its options before making a decision and taking action.

In the reactive control method, sensory inputs and outputs are tightly coupled, enabling the robot to respond quickly to changing and unstructured environments. This approach is known as "Don't Think, Just Act." Reactive control operates on the principle of stimulus-response, requiring neither learning nor the maintenance of a world model. Instead, it relies on a set of pre-programmed rules that minimize computational effort. These rules are mapped to the robot's controller, using minimal internal states to create a reactive control system capable of handling complex and unstructured environments while delivering fast, real-time responses. Reactive systems can quickly adapt to rapidly changing environments with minimal processing power [10].

Hybrid control combines the benefits of both reactive and deliberative control, allowing the robot to react in real time while also employing rational and optimal decision-making [11]. This approach is known as "Simultaneously Think and Act." The hybrid control system integrates reactive elements, such as simultaneous condition-action rules, with deliberative decision-making, which must be coordinated to produce coherent outcomes. This coordination can be challenging because the reactive component must respond quickly to the robot's immediate needs, such as avoiding obstacles while moving toward a target using direct sensory data and signals. Meanwhile, the deliberative component uses abstract, symbolic representations of the environment and operates on a slower time scale to guide the robot toward more efficient and optimal goals and trajectories. If an unexpected challenge arises, the reactive system may need to override the deliberative system, but the deliberative system should still inform the reactive system to ensure the most effective response.

A behaviour-based control system is a type of control system for robots that is composed of a collection of distributed modules known as behaviours [12]. These modules interact with one another to accomplish a desired action, with the ultimate goal of achieving a specific objective. The approach underlying this system is based on the concept of “Think the Way You Act,” where the robot’s behaviours are developed through trial-and-error interactions with its environment. These behaviours are typically defined by the programmer and organized into control modules that group together constraints to achieve and maintain a goal. This approach offers a flexible and adaptable means of controlling robots in complex and dynamic environments, enabling them to make decisions based on current conditions and adjust their actions accordingly. By utilizing behaviours grounded in the robot’s environment and experience, the behaviour-based control system provides a more intuitive and effective method for controlling robotic systems [13]. Each behaviour receives inputs from sensors or other behaviours and provides outputs to other behaviours or the robot’s actuators [14].

Implementing animal aggression behaviour in robotics involves creating robotic behaviour models that accurately mimic the aggression patterns observed in animals. This includes behaviours associated with Fear, Escape, Attack, and Immobility states, as well as animals familiarity with other animals and their surroundings. To achieve this, it is crucial to study and analyze animal behaviour in various situations and contexts, such as their familiarity with other animals, proximity to them, and past experiences. This understanding can then be translated into the design of robotic behaviour models that reflect similar behavioural patterns. For example, animals may exhibit a strong fear response when unfamiliar with another animal, prompting them to escape from the area. These physiological and behavioural responses can be incorporated into the design of robotic systems, enabling them to respond appropriately to perceived threats or dangerous situations. Similarly, an animals attack behaviour may involve aggressive posturing, vocalizations, and physical attacks. By observing and analyzing such behaviours in animals, robotic behaviour models can be developed to replicate these aggression patterns. Incorporating animal familiarity with other animals and their surroundings is also essential in developing effective robotic behaviour models. This may involve implementing recognition algorithms that allow robots to identify and respond to specific animals, as well as integrating mapping and navigation tools to enable robots to navigate their surroundings and avoid obstacles.

II. Ethological Behavioural Models

Ethology, the scientific study of animal behaviour, focuses on how animals interact with their environment and with each other [15]. Ethological models, essential for understanding and predicting animal behaviour, have become foundational in the development of behaviour-based control systems for robots. These models are based on the principle that natural selection shapes behaviour, with those behaviours most adapted to specific environments more likely to be passed on to future generations. This approach is crucial in ecology and animal behaviour studies, where models like predator-prey interactions help explain the dynamics of species populations in natural habitats.

In robotics, there is growing interest in leveraging ethological models to overcome the limitations of traditional robotic behaviour systems. Ethologists such as Baerends, Tinbergen, and Lorenz have developed models that describe animal behaviour and the processes behind it, which are now being explored in robotics. This interdisciplinary collaboration enables roboticists to create more adaptive systems by incorporating biologically inspired behaviour models. Conversely, robots offer ethologists a unique platform to test and refine their behavioural hypotheses.

This synergy between ethology and robotics, as discussed in [16] and [17], highlights shared concepts such as sensors, actuators, targets, and navigation, albeit studied differently in each field. Ethology employs a systematic, scientific approach to observing and understanding natural behaviours, while robotics takes a synthetic approach, integrating these behaviours into robots through artificial sensors and actuators. Despite their differing methodologies, both fields contribute to a deeper understanding of behaviour and its applications.

III. Fuzzy Behaviour-based System

One possible way for implementing ethologically inspired behavioural models is the adaptation of Fuzzy Behaviour-based Systems [18]. A Fuzzy Behaviour-based System is a high-tech computer system that uses fuzzy logic to control how robots and other agents act in complex, changing settings. It handles degrees of truth or membership values, allowing for more complex decisions. This adaptability is crucial for creating adaptive behaviours like those seen in animals. Different behaviour units control actions, such as avoiding, aggressive, or exploring, and fuzzy rules join their outputs to make the system behave logically. The Fuzzy Behaviour-based System is a structure built upon a network of fuzzy rule-based systems. Fuzzy rule bases are useful in the research of animal behaviour, allowing for complex interactions and self-driving systems to adapt to changing environments [19], [20]. A fuzzy rule-based system is an expert system where knowledge representation is in the structure of production fuzzy rules, such as **If** *[conditions]* and **Then** *[actions]* statements. For example, the level of “Fear” in a behaviour model can be described in terms of **IF Then** statements. E.g.:

If AFTP=*Low* **And** AFTA=*Low* **And** ADTA=*Low*
Then FEAR=*High*

where antecedent variable AFTP is the Animal Familiarity Towards Place, AFTA is the Animal Familiarity Towards Another, and ADTA is the Animal Distance Towards Another Animal.

The structure of a Fuzzy Behaviour-based System [21] consists of main modules, such as the Behaviour Coordination or Arbitration, the Behaviour Fusion, and the Component Behaviours themselves. Figure 1 illustrates a possible Fuzzy Behaviour-based System structure. In the case of the Fuzzy Behaviour-based System, each of the main components and the behaviour components is defined as fuzzy rule-based systems (Fuzzy Logic Controller – FLC on the figure).

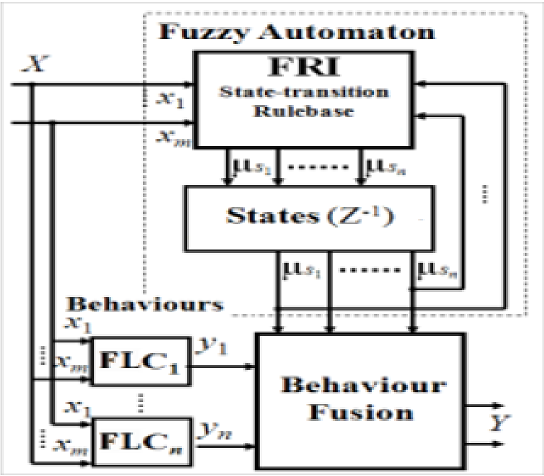


Fig. 1. The applied Fuzzy Behaviour-based System. [21]

Behaviour Coordination (Arbitration): This component is crucial in determining which behaviour should control the robot's operation at any given time, selecting tasks based on the current objectives and external conditions. Behaviour coordination, often referred to as arbitration, is a technique employed in autonomous systems design, particularly in robotics, to resolve conflicts between competing behaviours. In such systems, multiple behaviours can be active simultaneously, leading to conflicts when they compete for the same resources or interfere with one another. Behaviour coordination mechanisms are implemented to resolve these conflicts, ensuring smooth and efficient system operation by prioritizing behaviours and allocating resources to ensure successful task execution.

Various methods for behaviour coordination exist, each with its advantages and limitations. The one common approach which is often used is the hierarchical method, where behaviours are structured in a hierarchy, with higher-level behaviours taking precedence over lower-level ones. In this method, if lower-level behaviours conflict with higher-priority ones, the system will override the lower-level behaviours. In some instances, multiple behaviours may be activated concurrently, as seen in figure 2 fuzzy behaviour coordination. This approach involves context-dependent blending, a mechanism that allows for various patterns of behaviour combinations, such as following a target while avoiding obstacles. Decisions between behaviours are made based on the current situation by applying fuzzy logic [22].

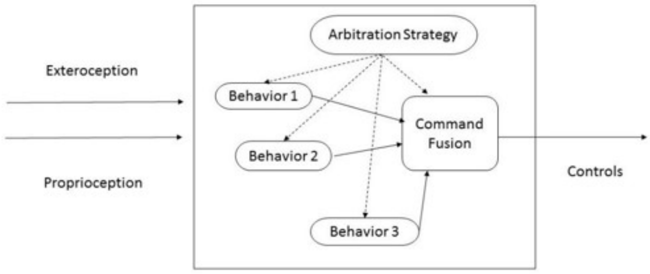


Fig. 2. The architecture of behaviour arbitration. [22]

Behaviour fusion refers to the process of combining the outcomes of behaviour coordination. For example, if a robot navigating a path encounters an obstacle, the arbitration mechanism will prioritize the obstacle avoidance behaviour. However, in some scenarios, behaviour fusion alone may not suffice to resolve conflicting behaviours. In such cases, a fuzzy rule-based system can be employed to assess conflicting conditions and determine which behaviour to prioritize [23]. Fuzzy behaviour fusion has been successfully applied across various domains, including robotics, autonomous vehicles, and healthcare [24], [25]. For instance, in autonomous vehicles, fuzzy behaviour fusion integrates data from multiple sensors, such as cameras and lidar, to estimate the vehicle's path and speed. Generally, fuzzy behaviour fusion is a powerful computational technique that enables the synthesis and integration of complex information from diverse sources, facilitating more nuanced and accurate predictions and decision-making.

IV. Implementation Guidelines

A behaviour-based system is built upon a series of interacting shared modules, known as behaviours, which collectively form the desired system-level behaviour. These behaviours are models of the robot's operation in specific situations, describing its interactions with the environment [26]. Social robots are designed to interact comfortably with humans and adapt to human social environments. Human-dog interactions can serve as the basis for behavioural models that create interactive capabilities for social robots. For example, just as dogs interact with humans in various situations and environments, social robots can be programmed to exhibit similar behaviours. A dog's behaviour and reactions can be recorded and described by humans [27], and if humans can comprehend these actions, they can also infer the corresponding conditions.

Developing Ethologically Inspired Fuzzy behaviour-based Systems for replicating animal aggressive behaviours in robotics requires a systematic approach that integrates ethology, fuzzy logic, and robotics knowledge. Initially, we conduct a comprehensive literature review to establish a robust theoretical foundation, with a particular emphasis on Archer's ethological model of aggression and fear in vertebrates, the principles of fuzzy logic, and their application in behaviour-based robotics. We then transform Archer's model into a fuzzy logic framework, linking significant behavioural components to fuzzy rules that effectively manage the imprecise and variable nature of aggression. The development phase involves constructing a fuzzy inference system that processes sensory inputs and produces appropriate behavioural outputs. Integrating the Fuzzy behaviour Description Language (FBDL) facilitates smooth and efficient interaction between the robot's control system and its environment. The accuracy of the model in replicating animal-like aggressive behaviours is visualized using the Robot Operating System (ROS), Gazebo, and RViz. This research aims to create a durable and adaptable robotic system capable of accurately imitating and managing aggressive behaviours by leveraging the complex dynamics observed in animal environments. Ultimately, the system can be applied in real-life scenarios to evaluate its effectiveness and adaptability.

A. *Implementing "Aggression"*

The goal is to create a fuzzy behaviour-based model of aggression based on the ethological model described in [28]. This model, developed by Archer in his paper "The Organization of Aggression and Fear in Vertebrates: Perspectives in Ethology," is a control theory-based ethological model, see figure 3. This model can help to provide insight into the underlying motivations for aggressive and fear behaviours. It provides a structured decision-making framework for animal behaviour, particularly in contexts involving aggression, fear, and responses to stimuli. The model comprises the following components:

Expectation Copy: The animal forms an expectation regarding the actions of the other animal. This anticipation is grounded in the animal's prior experiences with others, its understanding of animal behaviour, and its present internal state, such as its level of arousal.

Input: The animal receives sensory input from the other animal, including details like its size, posture, and movements.

Orientation Response: Upon receiving sensory input, the animal repositions towards the other animal and evaluates the situation.

Discrepancy: The animal compares the input it receives with its expectation. If an inconsistency arises between the two, the animal experiences heightened stimulation and may transition into a fight-or-flee state.

Decision Process 1 - Fear or Attack?: The animal weighs the options of responding with fear or launching an attack. This decision is influenced by several factors, such as the size of the discrepancy, the animal's hormone levels, past fighting experiences, and current internal state.

Attack: If the animal chooses to attack, it will initiate aggressive behaviour.

Environmental Consequences of Behaviour: The animal's actions will result in environmental outcomes. For instance, if the animal launches an attack on another, the other may flee.

Decision Process 2 - Escape or Immobility?: If the animal decides not to attack during Decision Process 1, it must decide whether to escape or immobility. This determination considers factors like the animal's hormonal state, the location of the other animal, and the animal's perceived ability to flee.

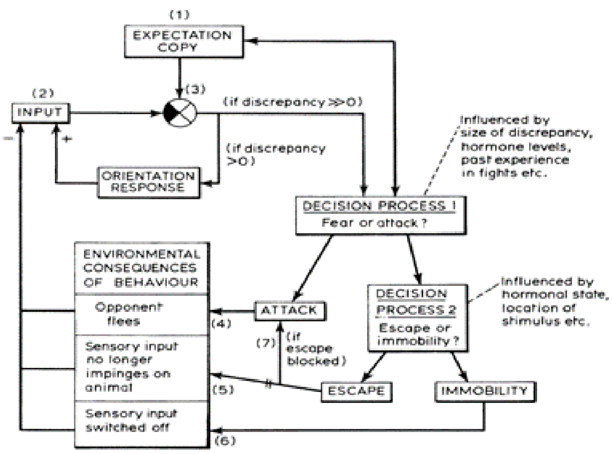


Fig. 3. Archer organization model [28].

Escape: If the animal decides to escape, it will try to get away from the other animal.

Sensory Input No Longer Impinges on the Animal: If the animal chooses to escape, then the sensory input from the other animal no longer affects the animal's senses.

If Escape is Blocked: If no escaping path exists, it will become aggressive and decide to attack.

Immobility: When the animal chooses not to attack and escape, it enters a state of immobility, which subsequently leads to the Sensory Input Switched Off:

Sensory Input Switched Off: The animal disengages from reacting to the sensory input provided by the other creature. In short, it means animals will not do anything at all.

The Archer Control Theory model provides a framework for understanding how systems function and how they can be controlled to achieve specific goals. According to this model, animals regulate their behaviour in response to various internal and external influences within the context of motivation. A simplified version of the control theory model of aggression and fear in vertebrates suggests that these behaviours are governed by two conflicting control systems: the aggression system and the fear/anxiety system. These two systems are thought to be in dynamic equilibrium, with the balance between them determining an animal's behavioural response. This model indicates that a complex interplay between internal and external factors influences these behaviours. The balance between the aggression and fear/anxiety systems can shift depending on the animal's current needs and environment.

Animal aggression is complex, involving elements such as Attack, Escape, and Immobility. FSMs offer a powerful method for simulating this behaviour because they can model the ambiguity and imprecision inherent in animal behaviour. Implementing animal aggression using a fuzzy state system requires several stages. First, we must define the animal states. In this context, the states can be categorized as Attack, Escape, and Immobility each representing a different behavioural response to a specific stimulus. Next, the inputs to the system must be defined. These inputs can include various stimuli, such as the presence of a predator or another animal in the animal's vicinity. Fuzzy logic can be employed to express the uncertainty surrounding certain inputs. For example, the input "presence of another animal" could be represented as a fuzzy set with membership functions like *"Low"* and *"High"* depending on the level of familiarity. After defining the states and inputs, we can establish the rules that govern how the states transition over time. These rules can also be represented using fuzzy logic. For instance, a rule might be stated as "The transition to Escape is high if the input "familiarity with another animal is low" and "familiarity with the environment is low." The degree of membership for each transition can be expressed using linguistic terms like "high" and "low." Finally, we define the system's outputs. These outputs correspond to the behaviours that the animal may exhibit in response to the stimuli. For example, the output "attack" could be linked to the aggressive state, if "familiarity with another animal and with the environment is low." In summary, implementing animal aggression behaviour using an FSM involves defining the states, inputs, rules, and outputs of the system. Fuzzy logic allows us to capture the ambiguity and imprecision of animal behaviour, providing a powerful tool for simulating such behaviours and developing strategies for managing animal aggression in various situations.

To implement the ethologically inspired behaviour model described above, we examine aggressive behaviour in animals with the following aims: First, we must categorize the circumstances in which aggression occurs. Second, we need to establish that these circumstances also trigger reactions related to Fear, Attack, Escape, Immobility, and distress communication. Third, we propose that these circumstances share specific characteristics, allowing for the development of a general theory on the causes of aggressive and fear-related behaviours. Fourth, we consider additional factors—such as internal physiological and motivational states, past experiences, and external variables—that may influence the likelihood of aggressive and fearful behaviours occurring. To conduct this analysis, we will employ a fuzzy behaviour model inspired by ethology. Before starting the implementation, we have defined specific terms below, which can also be expressed as fuzzy rules.

State Variables: The fuzzy "Aggression" behaviour model has four state variables. Three of them, the "Attack", "Escape," and "Immobility," have related behaviour components, and one, the "Fear," is a hidden state variable (see example in Fig. 4.).

"Fear"is an animal's physiological, behavioural, and emotional response to stimuli it comes across. For example, when an animal is terrified, it will display changes in body posture and activity. The scared animal may adopt protective body postures such as lowering the body and head, bringing the ears closer to the head, widening the eyes, and tucking the tail beneath the body. In our simplified model, fear has no related behaviour component, i.e., it is not observable independently from the environment but affects the other three state variables.

"Attack" refers to a rapid movement addressed at a specific stimulus that frequently results in physical damage to that stimulus, such as biting, hitting, pecking, and so on, but excludes such actions when they are related to food acquisition.

"Escape" any response intended to move away is referred to as Escape. Animals engage in escape behaviour when an animal's life is in danger, which may include rushing away from a threat in the environment.

"Immobility" is when an animal shows no signs of motion. This might be generated in a fear-conditioning experiment as a trained reaction to an aversively conditioned signal, or it could be elicited in response to unexpected stimuli that would be linked with a predator.

Observations: Following the "Aggression" ethological model described in [25], in our simplified fuzzy behaviour model, the four state variables depend on the following observations:

"Animal Familiarity Towards Place" (AFTP): This is defined as the level of familiarity an animal has with the place. These circumstances might occur when an animal enters a familiar or unfamiliar environment. Fear behaviour is most common when an animal enters an unknown environment, but attacking behaviour can also happen if a suitable target is attacked.

"Animal Familiarity Towards another Animal" (AFTA): The level of familiarity of an animal concerning another animal. These circumstances can occur in familiar or unfamiliar environments, i.e., when an animal is familiar with a place and some unknown animal comes close to an animal or enters another's familiar area; in this case, the animal shows fear and can also show attack behaviour.

"Animal Distance Towards another Animal" ADTA): How far is another animal? In simple terms, we can say the level of distance towards another animal. These circumstances can occur in different ways, such as familiar or unfamiliar with a place and familiar or unfamiliar with another animal, i.e., when an animal is unfamiliar with a place, another animal and the distance towards another animal is close in this case, animal shows high fear and can also show attack behaviour as well if there is no escape path existing.

"Animal Familiarity Towards Object" (AFTO): The animal's familiarity with an object. This situation occurs in an animal's familiar and unfamiliar environment, like when a moving object comes close to an animal or when the distance between the animal and the object decreases in an unfamiliar place. Also, when a novel object enters an animal's familiar place, these include the conventional territorial issue and a wide range of other scenarios such as fear, Attack, and escape behaviours. This observation (and also ADTO) serves as a robotic extension of the original model by Archer by considering that the appearance of a non-living object cause territorial issues for robots (i.e., non-living objects).

"Animal Distance Towards Object" (ADTO): The level of distance from an animal towards the object. This situation occurs in animal familiarity and unfamiliarity with the place and towards the object, such as when an unfamiliar moving object comes close to an animal, and the animal is unfamiliar with the place; in this case, various scenarios occur, such as fear, Attack, and escape behaviours.

“Escape Path Exists” (EPE): The level of a possible escaping path for the animal. This situation occurs when another animal or moving object approaches, and if the animal’s escaping path is not blocked, then the animal’s only option is to escape from that environment. When the possibility of Escape is blocked, the attack behaviour is mostly to occur, even if the animal shows broad signs of fear behaviour such as painful, stressful, or threatening stimuli.

“Positive Impact With respect to Previous Experience” (PIWPE): The degree of positivity and negativity associated with past experiences. In other words, it is the past positive and negative feelings of the animal that relate to the previous attacks. In this situation, the animal remembers his last feedback. Previous interactions are crucial in determining how an animal would react to a problem that could trigger attack or fear behaviour.

B. *The fuzzy model for the “Aggression” behaviour*

For implementing the fuzzy behaviour model of the “Aggression” behaviour, the Fuzzy Behaviour Description Language (FBDL) [29] was applied. The FBDL follows the concepts of fuzzy rule-based systems, Fuzzy Rule Interpolation (FRI), and their relationships to build behaviour components and behaviour coordination. The rule-based design makes knowledge representations comprehensible and self-explanatory for humans. The fuzziness and related Linguistic Term fuzzy set notion also improve human comprehension when variables are described on continuous universes. Having the FBDL description of the fuzzy behaviour model, the model can be directly evaluated numerically. The FBDL code can be performed directly on a system or, with some additional measurement data, can be used as an object for machine learning parameter optimization algorithms.

The FBDL defines the universes of the input and state variables, their linguistic terms (fuzzy sets applied in the fuzzy rule-bases), and the fuzzy rule-bases.

If we have an observation, e.g., the level of the “Animal Familiarity to the Place,” which is an input universe having two linguistic terms *Low* and *High* then giving a symbol name AFTP, the FBDL definition has the following form:

universe: AFTP
description: The Animal’s Level of Familiarity with the Place.
Low 0 0
High 1 1
end

A fuzzy rule in a rule-base determining, e.g., the level of the “Fear” hidden state-variable in the function of the level of the animal familiarity to the place, to the other animal, and the approaching object, could be the following in fuzzy rule format:

If AFTP=*High* **And** AFTA=*High* **And** AFTO=*High* **Then** FEAR=*Low*

where as AFTP is Animal Familiarity to the Place, AFTA is Animal Familiarity Towards Another, and AFTO is Animal Familiarity Towards Object are antecedent variables.

The same rule in FBDL format:

Rule *Low* **When** “AFTP” is *High* **And** “AFTA” is *High* **And** “AFTO” is *High* **end**

The fuzzy model of the “Aggression” behaviour in FBDL format. The FBDL definition of the AFTP, AFTA, AFTO, ADTA, ADTO, PIWPE, EPE input and the FEAR, ATTACK, ESCAPE, IMMOBILITY state variable universes are similar (see e.g. AFTP and FEAR):

universe: AFTP
Low 0 0
High 1 1
end
universe: FEAR
Low 0 0
High 1 1
end

The FBDL definition of the state rule-bases is described below one by one. It is represented based on different scenarios such as (a) animal familiarity with a place, object, and another animal, (b) a moving object or animal approaching an animal too closely (individual distance intrusion), (c) a new object or animal enters another’s familiar territory: this can encompass the usual territorial issue and various scenarios, (d) entering an unfamiliar environment: fear typically occurs, (e) a familiar object in a strange setting, (f) degree of positiveness associated with the previous Attack.

In fuzzy rule-base format, the FEAR Fuzzy Rule-base ($\mathbf{R}_{\text{FEAR}}$) is the following:

If AFTP=*Low* **And** AFTA=*Low* **And** AFTO=*Low* **Then** FEAR=*High*
If AFTA=*Low* **And** ADTA=*Low* **And** EPE=*Low* **Then** FEAR=*High*
If AFTO=*Low* **And** ADTO=*Low* **And** EPE=*Low* **Then** FEAR=*High*
If AFTP=*Low* **And** EPE=*Low* **And** PIWPE=*Low* **Then** FEAR=*High*
If AFTP=*High* **And** AFTA=*High* **And** AFTO=*High* **Then** FEAR=*Low*
If AFTA=*High* **And** ADTA=*High* **And** EPE=*High* **Then** FEAR=*Low*
If AFTP=*High* **And** AFTA=*High* **And** EPE=*High* **And** PIWPE=*High* **Then** FEAR=*Low*

where AFTP, AFTA, ADTA, AFTO, ADTO, EPE, PIWPE are the antecedent universes, FEAR is the consequent universe, *Low* and *High* are fuzzy linguistic terms in the corresponding universes.

The same FEAR rule-base in FBDL format appears as:

RuleBase “FEAR”
Rule *High* **When** “AFTP” is *Low* **And** “AFTA” is *Low* **And** “AFTO” is *Low* **end**
Rule *High* **When** “AFTA” is *Low* **And** “ADTA” is *Low* **And** “EPE” is *Low* **end**
Rule *High* **When** “AFTO” is *Low* **And** “ADTO” is *Low* **And** “EPE” is *Low* **end**
Rule *High* **When** “AFTP” is *Low* **And** “EPE” is *Low* **And** “PIWPE” is *Low* **end**

Rule *Low* **When** "AFTP" is *High* **And** "AFTA" is *High* **And** "AFTO" is *High* **end**
Rule *Low* **When** "AFTA" is *High* **And** "ADTA" is *High* **And** "EPE" is *High* **end**
Rule *Low* **When** "AFTP" is *High* **And** "AFTA" is *High* **And** "EPE" is *High* **And** "PIWPE" is *High* **end**
end

In fuzzy rule-base format, the ATTACK Fuzzy Rule-base ($\mathbf{R}_{\text{ATTACK}}$) is the following:

If AFTA=*Low* **And** ADTA=*Low* **And** EPE=*Low* **Then** ATTACK=*High*
If AFTO=*Low* **And** ADTO=*Low* **And** EPE=*Low* **Then** ATTACK=*High*
If AFTP=*Low* **And** ADTA=*Low* **And** ADTO=*Low* **And** EPE=*Low* **Then** ATTACK=*High*
If FEAR=*High* **And** EPE=*Low* **Then** ATTACK=*High*
If AFTP=*High* **And** AFTA=*High* **And** PIWPE=*High* **Then** ATTACK=*High*
If AFTP=*High* **And** AFTO=*High* **And** PIWPE=*High* **Then** ATTACK=*High*
If EPE=*High* **And** FEAR=*High* **Then** ATTACK=*Low*
If EPE=*High* **And** AFTP=*Low* **And** ADTA=*High* **Then** ATTACK=*Low*
If EPE=*High* **And** AFTA=*Low* **And** ADTA=*High* **And** PIWPE=*Low* **And** ADTO=*High* **Then** ATTACK=*Low*
If EPE=*High* **And** AFTO=*Low* **And** ADTO=*High* **And** PIWPE=*Low* **Then** ATTACK=*Low*
If AFTA=*Low* **And** AFTP=*Low* **And** AFTO=*Low* **And** EPE=*High* **Then** ATTACK=*Low*

The antecedent universes are AFTP, AFTA, ADTA, AFTO, ADTO, EPE, PIWPE, FEAR. The consequent universe is ATTACK, and Low and High are fuzzy linguistic terms in the corresponding universes.

In fuzzy rule-base format, the ESCAPE Fuzzy Rule-base ($\mathbf{R}_{\text{ESCAPE}}$) is the following:

If EPE=*High* **And** FEAR=*High* Then ESCAPE=*High*
If EPE=*High* **And** AFTP=*Low* **And** AFTA=*Low* **And** AFTO=*Low* **Then** ESCAPE=*High*
If EPE=*High* **And** AFTA=*Low* **And** ADTA=*High* **And** PIWPE=*Low* **Then** ESCAPE=*High*
If EPE=*High* **And** AFTO=*Low* **And** ADTO=*High* **And** PIWPE=*Low* **Then** ESCAPE=*High*
If EPE=*High* **And** AFTP=*Low* **And** ADTA=*High* **And** ADTO=*High* **And** PIWPE=*Low* **Then** ESCAPE=*High*
If FEAR=*Low* **And** EPE=*Low* **Then** ESCAPE=*Low*
If FEAR=*Low* **And** PIWPE=*High* **Then** ESCAPE=*Low*
If AFTA=*High* **And** AFTO=*High* **And** AFTP=*High* **And** PIWPE=*High* **Then** ESCAPE=*Low*
If AFTA=*High* **And** ADTA=*High* **And** PIWPE=*High* **And** EPE=*Low* **Then** ESCAPE=*Low*
If AFTO=*High* **And** ADTO=*High* **And** PIWPE=*High* **And** EPE=*Low* **Then** ESCAPE=*Low*

where AFTP, AFTA, ADTA, AFTO, ADTO, EPE, PIWPE, FEAR are the antecedent universes, ESCAPE is the consequent universe, and *Low* and *High* are fuzzy linguistic terms in the corresponding universes.

In fuzzy rule-base format, the IMMOBILITY Fuzzy Rule-base ($\mathbf{R}_{\text{IMMOBILITY}}$) is the following:

If FEAR=*Low* **And** EPE=*Low* **Then** IMMOBILITY=*High* **If** AFTA=*Low* **And** ADTA=*High* **And** EPE=*Low* **Then** IMMOBILITY=*High*
If AFTO=*Low* **And** ADTO=*High* **And** EPE=*Low* **Then** IMMOBILITY=*High*
If AFTP=*Low* **And** ADTA=*High* **And** EPE=*Low* **Then** IMMOBILITY=*High*
If AFTP=*Low* **And** AFTA=*Low* **And** PIWPE=*Low* **Then** IMMOBILITY=*High*
If EPE=*High* **And** FEAR=*High* **And** PIWPE=*Low* **Then** IMMOBILITY=*Low*
If EPE=*High* **And** AFTA=*Low* **And** ADTA=*Low* **And** PIWPE=*Low* **Then** IMMOBILITY=*Low*
If EPE=*High* **And** AFTO=*Low* **And** ADTO=*Low* **And** PIWPE=*Low* **Then** IMMOBILITY=*Low*

The antecedent universes are AFTP, AFTA, ADTA, AFTO, ADTO, EPE, PIWPE, FEAR, and the consequent universe is IMMOBILITY, with the fuzzy linguistic terms *Low* and *High* in the corresponding universes.

Several variables can influence whether an animal will exhibit Fear, Escape, Attack, or Immobility behaviours in a given situation. These variables can be categorized into internal characteristics and behavioural outcomes.

"Internal characteristics" that may impact an animal's tendency to exhibit fear or attack behaviours include: (a) The degree of discrepancy between expectations and observations: A significant difference between what an animal expects and what it observes can trigger fear and escape behaviours, as the animal perceives a potential threat. Conversely, if the observed stimulus closely matches expectations, the animal may exhibit attack behaviours instead. This highlights how animals respond to uncertainty and familiarity in their environment. (b) The degree of positive motivation from previous experiences: An animal's positive motivation or reinforcement from earlier experiences influences its present behaviour. When this level of positive motivation is high, the animal is more likely to attack rather than escape in a given situation. Prior positive reinforcement may lead an animal to fight rather than flee. (c) Experiential factors: Early life situations, social isolation, and previous reinforcements significantly impact an animal's decision to either attack or escape when faced with a frightening circumstance. Early experiences and social interactions shape their responses, while past reinforcements guide their decision-making. These elements contribute to the complexity of animal behaviour and enhance our understanding of why animals respond the way they do in various situations.

"Behavioural Outcomes" that may affect specific behaviours include: (a) Properties of the target: The characteristics of the object being attacked or defended against, such as its size, movement, and location, can influence behaviour. For example, the size (whether it is large or small), the ease of movement (how easily it can be moved), and the proximity (how close or far it is from the attacker) are factors to consider. (b) Preference for passive or active responses: Animals often have a preferred course of action when faced with danger.

They may choose to avoid the threat passively by remaining still or to escape by moving away. The degree and location of sensory discrepancies—anything that seems abnormal in their environment—can impact this choice. (c) The possibility of escape: The likelihood of escaping from danger affects behaviour. If escape is physically impossible (for instance, if an animal is trapped in an area with no way out), attack behaviours may become more likely as a form of self-defense.

Figure 4 represents the components of an animal's aggressive behaviour fuzzy model concerning all the possible components defined above, such as towards place, another animal, object, distance, etc.

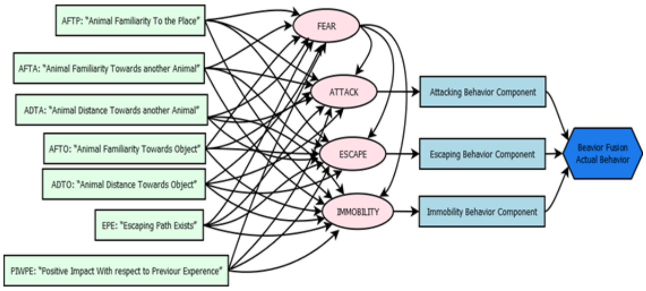
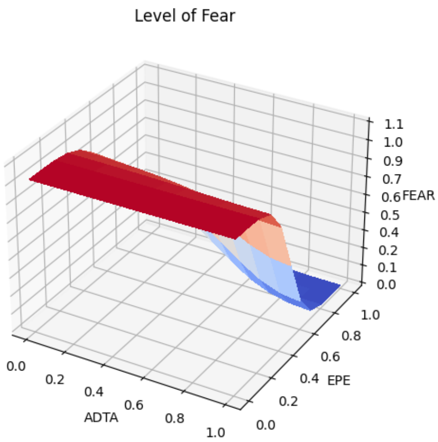
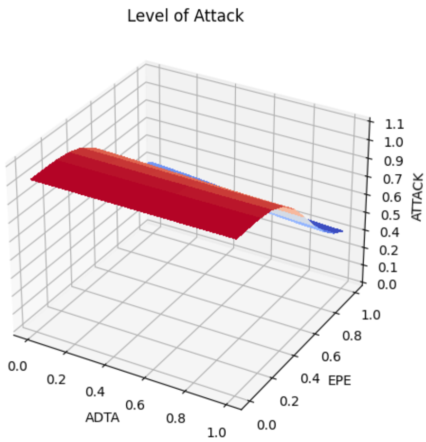


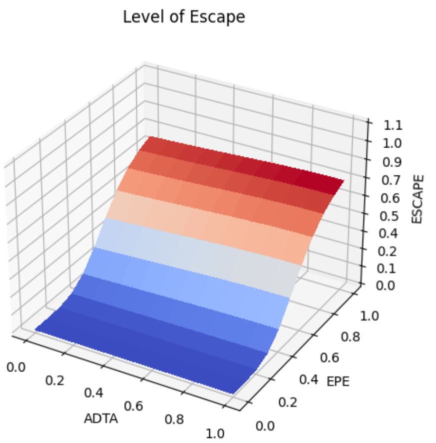
Fig. 4. Animal Aggressive Behaviour Fuzzy model.



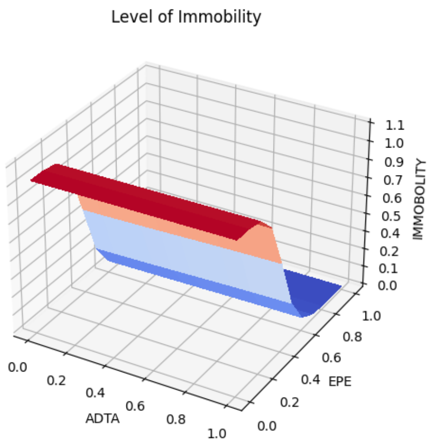
(a) Level of Fear Behaviour.



(b) Level of Attack Behaviour.



(c) Level of Escape Behaviour.



(d) Level of Immobility Behaviour.

Fig. 5. (a), (b), (c), (d): Graphical Representation of Behaviours

Figure 5 demonstrates some examples of the behaviour component level changes in the functions of the observations according to the fuzzy model of aggressive behaviour. All the graphs are based on the calculation of the FBDL [29] description given in this paper using the implemented FBDL functions publicly available in [30], [31]. We have taken two observations, ADTA and EPE changing from *Low* to *High* and the rest of the observations to be constant (i.e., the animal is highly familiar with the place and another animal: AFTP=*High*, AFTA=*High*, and less familiar with AFTO=*Low*, ADTO=*Low*, PIWPE=*Low*). Red color represents *High*, and blue represents *Low*. Figure 5(a) demonstrates the state change of "Fear" in the function of ADTA and EPE in this case. According to the graph, the FEAR will be *High* if no escape path exists. The approaching other animal is unfamiliar (AFTA=*Low*, EPE=*Low*) and *Low* if the animal is familiar with these states such as AFTA=*High*, AFTP=*High*, AFTO=*High*). The level of ATTACK behaviour (see Figure 5(b)) is *High* if the animal is not familiar with the approaching other animal, distance towards other animal is less, and there is no escape path exists (AFTA=*Low*, ADTA=*Low*, EPE=*Low*) and *Low* if escape path exists (EPE=*High*). The level of ESCAPE (see Figure 5(c)) is *High* if the animal is not familiar with the approaching another animal, not familiar with the place, and there is a high escape path exists (AFTA=*Low*, AFTP=*Low*, EPE=*High*) and *Low* if there is no escape path exists (EPE=*Low*). The level of IMMOBILITY (see Figure 5(d)) as a decision instead of attacking is *High* if the animal is not familiar with the approaching another animal, distance towards another animal is less, and there is no escape path exists (AFTA=*Low*, ADTA=*Low*, EPE=*Low*) and *Low* if an escape path exists and distance towards another animal is *High* (EPE=*High*, ADTA=*High*).

Figure 6 illustrates the trajectories of Robot_1 and Robot_2, showcasing a sophisticated representation of animal Escape behaviour, based on fuzzy behaviour principles. This behaviour is well-suited for replicating animal-like actions in robotics. The blue trajectory of Robot_1 (R1) and the green trajectory of Robot_2 (R2) display intricate behavioural patterns similar to those observed in animals, with a particular focus on escape behaviours in response to the presence of another entity. The robots start at the following positions: Robot_1 begins at coordinates (0.5, 0.5), and Robot_2 starts at coordinates (6, 6). Robot_1 is tasked with moving closer to Robot_2's starting location, while Robot_2 is directed to approach Robot_1's initial position. This setup creates a scenario where both robots advance towards each other's initial positions.

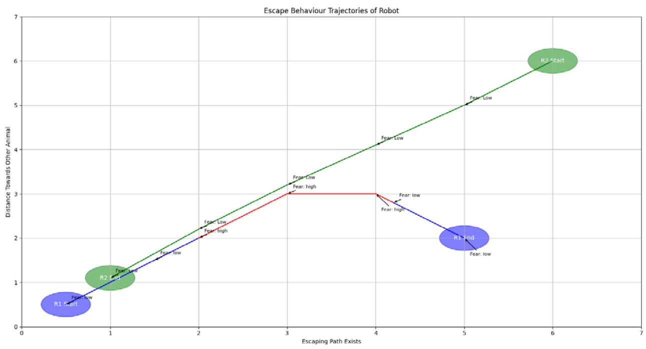


Fig. 6. Robot trajectories for the ESCAPE behaviour.

In this escape behaviour example, Robot_1 serves as the primary actor and will perform the escape behaviour. We assume that Robot_1 is initially unfamiliar with its environment, including Robot_2, which is fully acquainted with the surroundings. Upon entering the environment, Robot_1 exhibits a baseline level of fear due to its unfamiliarity. As the robots move and the distance between them decreases, a fuzzy logic-based system evaluates Robot_1's behavioural response, considering parameters such as the distance between the robots (ADTA), the FEAR level, and the availability of an escape route (EPE). When Robot_1 perceives that its proximity to Robot_2 has reached a critical threshold, its FEAR level is algorithmically increased. Subsequently, Robot_1 assesses the feasibility of an escape and, upon seeing an escape route, initiates an escape response. This response is visually represented by a shift in Robot_1's trajectory color to red, symbolizing heightened fear and the commencement of escape maneuvers, thus graphically indicating an increased state of alertness.

The synchronization and integration of behaviours are fundamental to the dynamics of the trajectories. The trajectories of both robots are interdependent, reflecting the behavioural coordination observed in animal interactions, where the actions of one organism provoke responses from another. The interactions between Robot_1 and Robot_2 influence various behaviours, such as movement toward a target and avoidance of potential threats, which, in turn, determine Robot_1's trajectory. This interaction results in a flexible and complex behavioural pattern that adapts to perceived changes in threat levels.

As the distance between the robots increases, Robot_1's response. The trajectories of Robot_1 and Robot_2 not only demonstrate the effectiveness of fuzzy logic in developing behaviour-based robotic systems but also provide a compelling model for emulating animal escape strategies. By integrating fuzzy rules, coordinating interactive behaviours, and synthesizing multiple actions into a cohesive response, this system offers valuable insights into the potential capabilities of advanced autonomous robotic systems. Such systems, capable of navigating and responding to complex environments similarly to biological entities, hold significant promise for applications in autonomous exploration and interactive robotics.

Figure 7 depicts the ATTACK behaviour trajectory between Robot_1 (R1) and Robot_2 (R2), utilizing a fuzzy behavioural architecture that emulates the dynamics of animal aggression. The fuzzy rule base within this framework facilitates the simulation of complex and uncertain interspecies interactions, particularly in the context of aggression. In this scenario, each robot's behaviour is represented by a distinct color-coded fear level decreases, leading to a diminished escape response. During this phase, Robot_1 undergoes a behavioural shift, indicated by a change in its trajectory color back to blue, signaling a reduction in anxiety and the cessation of the escape path, illustrating their interactions over time and space. This mirrors the movement and interaction patterns observed among animals within a shared space. Initially, Robot_1's trajectory, starting at coordinates (1,1), is colored blue, reflecting typical non-aggressive behaviour. Robot_1's objective is to approach Robot_2, display aggression, and assert dominance. Robot_2's trajectory, represented by a green line at coordinates (5.5, 5.5), suggests an absence of fear. As the distance between Robot_1 and Robot_2 diminishes, Robot_1's trajectory shifts to red, signifying an escalation in aggression and the initiation of an attack, analogous to an animal transitioning from pursuit to combat.

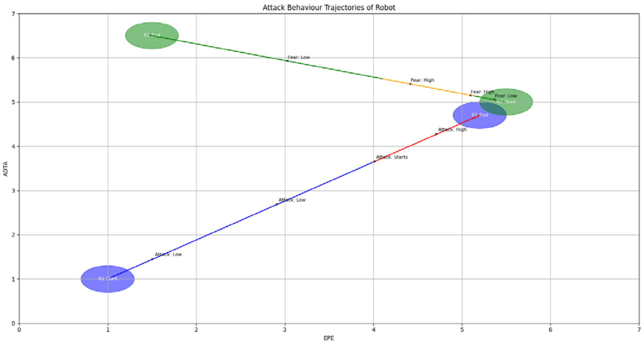


Fig. 7. Trajectories for the Attack Behaviour.

As Robot_1 approaches, Robot_2 begins to experience fear, which is visually represented by its trajectory turning orange, indicating a heightened fear response. This shift can be likened to an animal becoming increasingly anxious and defensive when it perceives a threat or rival, prompting it either to defend itself or flee. The changing colors in Robot_2's path signify its escalating fear and desire to avoid confrontation by retreating, particularly due to its unfamiliarity with Robot_1 and the decreasing distance between them. This interaction between the two robots mirrors animal behaviour, characterized by a complex interplay of stimuli and responses. The aggressive movements of Robot_1 elicit a fear-based reaction in Robot_2, governed by fuzzy rules that take into account factors such as proximity ADTA, environmental familiarity AFTP, and perceived threat levels AFTA. Consequently, Robot_1's behaviour adapts, becoming increasingly aggressive as it closes in on its target. Similarly, a fuzzy logic system modulates Robot_2's responses by evaluating its fear level, resulting in a retreat as the threat diminishes and a return to its original low-fear trajectory, represented by a green path. This pattern reflects the natural process by which animals regain composure once the perceived threat has subsided.

The trajectories of both robots underscore the sophistication of the FSM in emulating animal behaviours. The system effectively replicates complex actions such as aggression, fear, and survival strategies. This advancement is pivotal for the development of autonomous robotics, enabling robots to navigate and respond to complex environments by dynamically adjusting their behaviour in response to internal states and external stimuli. Moreover, this approach offers valuable insights into animal behaviour, facilitating ecosystem studies and the creation of intelligent machines capable of natural interactions with their surroundings.

The simulation of animal escape behaviour, as depicted in figures 8(a)–8(e), is based on the escape behaviour trajectory described above. It employs the Robot Operating System (ROS) in conjunction with tools such as Gazebo and Rviz to model the escape behaviour of robots designed to mimic animals. This simulation involves a sophisticated integration of robotic vision, decision-making processes, and movement, all orchestrated within a controlled virtual environment. A key element of this setup is the use of LIDAR (Light Detection and Ranging), a highly esteemed sensor in robotics for its ability to generate real-time, high-resolution 3D scans of the environment. In the escape scenario, LIDAR is crucial for the system's operation at high speeds, enabling instantaneous object detection and data collection from multiple angles. This capability is particularly important for the rapid and accurate identification of other entities, which is essential for timely and precise reactions.

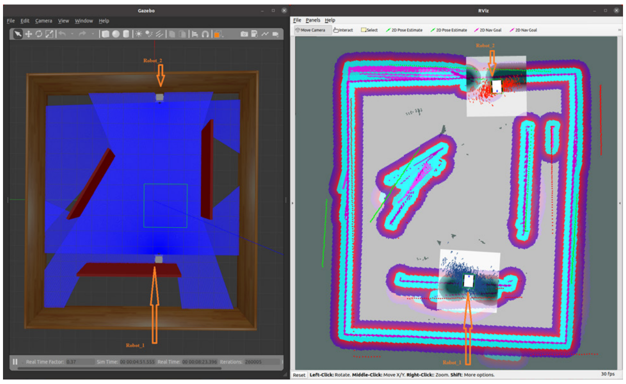
The simulated scenario involves two robots, designated as Robot_1 and Robot_2,, within a confined space containing walls and other objects. In this scenario, Robot_1, represented by blue dots, is positioned near an object, while Robot_2, indicated by red dots, is located near a wall. Robot_1 serves as the primary actor, with its behaviour and responses driving the sequence of interactions within the simulation. The trajectory and behaviour of Robot_1, as described earlier, illustrate the complex decision-making processes that underpin its actions, driven by fuzzy logic and real-time environmental data. This demonstrates the potential of such systems to replicate the adaptive and dynamic nature of animal escape behaviours.

The simulation designates the initial location of these animal robots, as seen in figure 8(a). The subsequent stages involve Robot_1 and Robot_2 approaching their respective starting positions, leading to a scenario where they progress towards each other. Figure 8(b) depicts the dynamic stage of the robots, capturing their movement. The experiment incorporates concepts such as behaviour fusion, behaviour coordination, and fuzzy component behaviour to analyze the system's performance. Fuzzy component behaviour specifically refers to the use of fuzzy logic for interpreting input data obtained from sensors such as LIDAR. In this instance, the robotic animals use data from laser scans to identify each other and calculate their relative distance.

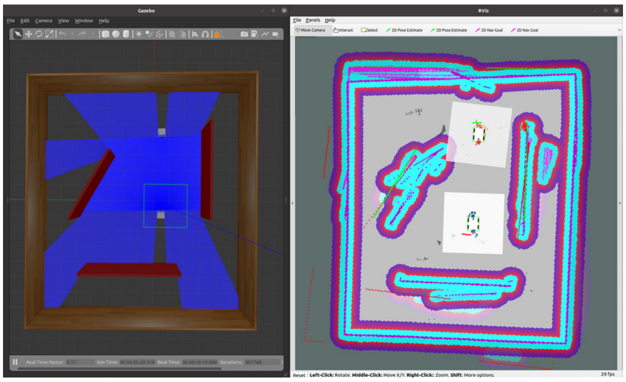
As the robots approach each other, as shown in figure 8(c), Robot_1 detects the presence of Robot_2 using its sensors and input data. The fear level of Robot_1 increases and is assessed using a fuzzy rule-based approach that considers factors such as the robot's familiarity with other robots, the surroundings, the distance to Robot_2, and the availability of escape route. Figure 8(d) illustrates the moment when Robot_1 escapes due to high fear and the presence of escape path.

behaviour coordination in this context refers to the synchronization of the robots actions to achieve a shared goal, such as escaping in this particular scenario. Robot_1's escape upon approaching Robot_2 is a result of its unfamiliarity with the environment and the other robot, as specified in the escape regulations. behaviour fusion combines the behaviours of both robots to achieve the specific objective of assisting Robot_1 in escaping.

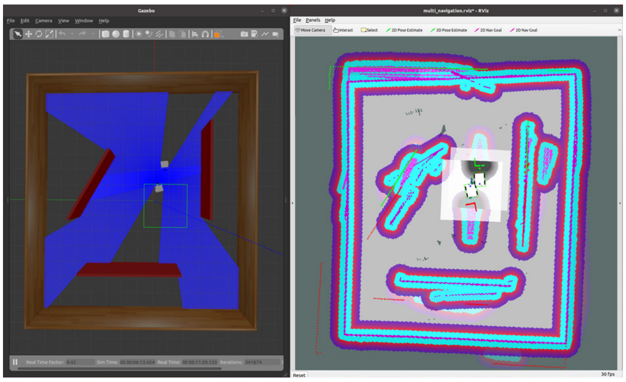
Figure 8(e) depicts Robot_1 successfully evading Robot_2, indicating that it is now at a safe distance. This result highlights the effectiveness of the fuzzy rule-based system and the principles of behaviour coordination in achieving the desired outcome.



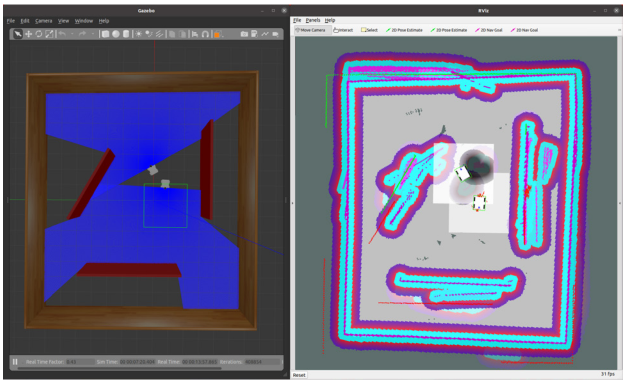
(a) Initial Position of Robots: both robots start at designated positions.



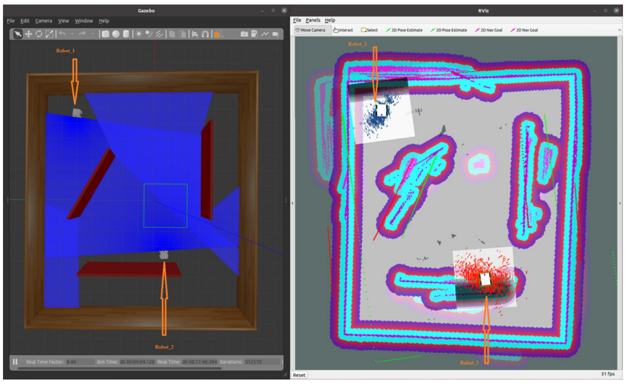
(b) Movement Stage: robots move towards each other.



(c) Detection and Fear Assessment: Robot_1 detects Robot_2 and assesses fear based on proximity and environment unfamiliarity.



(d) Escaping, High fear, and the presence of an escape route triggered Robot_1's Escape.



(e) Robot_1 successfully escapes, illustrating the effective use of fuzzy logic, behaviour coordination, and fusion.

Fig. 8. (a), (b), (c), (d), (e): Escape behaviour simulation

V. CONCLUSION

This paper presents a method for implementing an ethologically inspired animal behaviour model, "aggression," for robotic applications. It uses a Fuzzy Behaviour-based System to improve the realism and complexity of animals' escape behaviour models. We employ a fuzzy rule-based system to process input data, orchestrate different agents' actions, and amalgamate multiple agents' behaviours. ROS tools such as Gazebo and RVIZ were applied for visualization of the escape behaviour trajectories. The goal was to develop robots that could independently make decisions based on detailed sensory inputs, effectively emulating animal instincts and responses. The study also explores the dynamics of multi-agent systems and the intricate interactions among robots, which have profound implications for sectors like collaborative manufacturing, search and rescue operations, and surveillance. The presented methodology supports the development of adaptable, intelligent, and safe robotic systems applicable in various disciplines. The goal is to implement the animal aggression behaviour model from simulation to practical use in real-world robots, improving the scope of behavioural models and enhancing safety and intelligence to increase robot autonomy.

VI. ACKNOWLEDGEMENT

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